

# Performance Evaluation of Adaptive Ramp Metering Algorithms Using Microscopic Traffic Simulation Model

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ATMS Testbed Technical Report TTR3-14

This work was performed as part of the ATMS Testbed Research and Development Program of the University of California, Irvine.\* The contents of this report reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views of policies of the State of California. This report does not constitute a standard, specification, or regulation.

**June 2005**

\* In cooperation with the California Partners for Advanced Transit and Highways

# **Performance Evaluation of Adaptive Ramp Metering Algorithms**

## **Using Microscopic Traffic Simulation Model**

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## **Abstract**

Adaptive ramp metering has undergone significant theoretical developments in recent years. However, the applicability and potential effectiveness of such algorithms depend on a number of complex factors that are best investigated during a planning phase prior to any decision on its implementation. The use of traffic simulation models can provide a quick and cost-effective way to evaluate the performance of such algorithms prior to implementation on the target freeway network. In this paper, a capability-enhanced PARAMICS simulation model has been used in an evaluation study of three well-known adaptive ramp-metering algorithms, ALINEA, BOTTLENECK and ZONE. ALINEA is a local feedback control algorithm and the other two are area-wide coordinated algorithms. The evaluation has been conducted in a simulation environment over a stretch of the I-405 freeway in California, under both recurrent congestion and incident scenarios. Simulation results show that adaptive ramp-metering algorithms can reduce freeway congestion effectively compared to the fixed-time control. ALINEA shows good performance under both recurrent and non-recurrent congestion scenarios. BOTTLENECK and ZONE can be improved by replacing their native local occupancy control algorithms with ALINEA. Compared to ALINEA, the revised BOTTLENECK and ZONE algorithms using ALINEA as the local control algorithm are found to be more efficient in reducing traffic congestion than ALINEA alone. The revised BOTTLENECK algorithm performs robustly under all scenarios. The results also indicate that ramp metering becomes less effective when traffic experiences severe congestion under incident scenarios.

**CE Database Keywords:** Traffic management; Ramps; Performance evaluation; Simulation.

## Introduction

Ramp metering has been recognized as an effective freeway management strategy to avoid or ameliorate freeway traffic congestion by limiting access to the freeway. A variety of ramp metering algorithms have been proposed based on a variety of approaches that include: optimization techniques (Chen et al. 1974), automatic control (Papageorgiou et al. 1991), optimal control theory (Zhang et al. 1996) or artificial intelligence methods (Taylor et al. 1998 and Zhang et al. 1997). Although there have been significant theoretical developments in formulating ramp-metering policies, implementations based on such developments have been slow in coming.

In practice, modes of metering operation can be divided into two primary categories, fixed-time (or pre-timed) control and adaptive (or traffic responsive) control. In a fixed-time ramp-metering plan, metering rates are determined based on historical traffic information and established on a time-of-day basis. The adaptive ramp metering control can be further classified as local traffic responsive control and coordinated traffic responsive control. The metering rates under a local traffic responsive control are based on current prevailing traffic conditions in the vicinity of the ramp. Examples of local traffic responsive control are demand-capacity, occupancy control, and ALINEA (Papageorgiou et al. 1991). Coordinated traffic responsive ramp metering operation seeks to optimize a multiple-ramp section of a highway, often with the control of flow through a bottleneck as the ultimate goal. In a coordinated metering plan, the metering rates of a ramp are determined based on the prevailing traffic conditions of an extended section of roadway. More recently, advanced coordinated traffic-responsive ramp metering strategies, widely regarded as the natural evolution of localized control, has begun to be deployed. Notable instances of coordinated ramp-metering systems include ZONE in

Minneapolis / St. Paul, Minnesota (Lau, 1997), BOTTLENECK in Seattle, Washington (Jacobsen et al. 1989), HELPER in Denver, Colorado (Corcoran, et al., 1989), METALINE in Paris and Amsterdam (Papageorgiou et al. 1997), SDRMS in San Diego, California, and SWARM in Los Angeles and Orange County, California (Paesani et al. 1997).

Ramp metering control involves balancing the interests of local (arterial) and through (freeway) traffic, and thus its applicability, onsite deployment and operation continue to face political challenges that call for the cooperation of related parties. Because of the complexity of these coordinated ramp metering systems, their successful implementation depends both on such hardware (or ITS infrastructure) as communication system and loop detectors installed at specific locations and on software (such as the algorithm logic, the design and operational calibration of a ramp metering algorithm on the target freeway network). Studies show that significant benefits can be obtained from ramp metering only when implemented correctly and operated effectively (Pearce 2000). Therefore, questions related to whether ramp metering is warranted, which kind of ramp metering algorithm is suitable and how to calibrate and optimize the operational parameters, ought be investigated during a pre-implementation phase in order to ensure the success of the implementation.

The use of microscopic traffic simulation models can provide a quick and cost-effective way to evaluate the performance of a ramp control algorithm. Microscopic models feature the calculation and prediction the state of individual vehicles in continuous or discrete time-space and offer detailed descriptions of both road and traffic characteristics (acceleration lanes, merging, lane-changing, etc.) that are critical to ramp metering. Therefore, in this paper, we adopt one of the microscopic simulation models, PARAMICS (PARAllel MICroscopic Simulation), as our evaluation tool.

This paper is organized as follows. Section 2 presents the simulation environment, data acquisition, and model calibration. Section 3 provides the descriptions and parameter calibrations of the three ramp-metering algorithms that were evaluated: ALINEA, BOTTLENECK, and ZONE, as well as versions of BOTTLENECK and ZONE modified to incorporate ALINEA as the local controller. The evaluation results are discussed in Section 4. Section 5 concludes the paper with some remarks on the results.

## **Simulation Modeling**

### ***Capability-Enhanced PARAMICS Simulation***

PARAMICS is a scalable, ITS-capable high-performance microscopic traffic simulation package developed in Scotland (Smith et al. 1994). To evaluate adaptive ramp-metering algorithms, the capabilities of PARAMICS had to first be extended to enable its use. Specifically, for our evaluation study, two complementary components, ramp metering controller and loop data aggregator, were developed and incorporated into the PARAMICS simulation environment. This was accomplished using the Application Programming Interface (API) library through which users could customize and extend many features of the underlying simulation model.

The simulation environment is illustrated in Figure 1. The core of the simulation environment is the PARAMICS model (Build 3.0.7) and its associated API modules. The ramp meters are controlled by the ramp metering API, through which metering rates in the simulation can be queried and set by other API modules. The loop data aggregator emulates the data collection process of real-world loop detectors, typically with a thirty-second interval, and stores the aggregated loop data into our MySQL (Sequential Query Language) database. The adaptive ramp metering is implemented in PARAMICS as an API module that is built on top of these two

basic plug-in modules. At each time increment the adaptive algorithm API queries the MySQL database to obtain up-to-date traffic information provided by the loop data aggregator API and historical metering rates provided by ramp metering API. Then the next metering rate is computed based on the algorithm logic and sent back to the ramp metering API for implementation. The performance measure API is used for gathering measures of effectiveness (MOEs) for result analysis.

As shown in Figure 1, the hierarchical development of API enables customization and enhancements of various aspects of simulation modeling. The plug-in modules provide the user more freedom to control the simulation processes and hence overcome some challenges faced in modeling some ITS features. As a result, these algorithms, and even other advanced traffic management system (ATMS) applications, can be easily tested and evaluated in this capability-enhanced micro-simulation environment.

### ***Study Site and Data Acquisition***

The study site is a six-mile stretch of northbound freeway I-405, between junctions of freeway I-5 and Culver Drive, in Orange County, California. The network has seven entrance ramps, four exit ramps and one freeway-to-freeway ramp connecting freeway SR-133 with I-405, which is not metered. The schematic representation of the study site is illustrated in Figure 2. The line across the freeway lanes represents mainline detector, whose location is shown on the bottom by its post-mile. There are also detectors (which are not shown in the figure) located on entrance and exit ramps.

As a major freeway linking Orange County to Los Angeles, this section of freeway experiences heavy traffic congestion during peak hours. In the morning peak, the congestion derives from the large amount of traffic merging to freeway I-405 from freeway SR-133. In

addition, heavy traffic flow entering freeway I-405 from Sand Canyon Drive (i.e. on-ramp 3) and Jeffery Drive (i.e. on-ramps 4 and 5) causes another bottleneck at the downstream of on-ramp 5. Congestion at this bottleneck often spreads upstream, further deteriorating the congestion at the upstream bottleneck. Currently, this freeway section operates on time-of-day-basis fixed-time ramp control (based on a one-car-per-green principle). The metering plans in place are shown in Table 1.

The time-dependent OD demands, which are the inputs to PARAMICS simulation, were estimated based on the historical loop data. Loop data of May 22, 2001 were used for the calibration of our network model. Loop data from May 22, 2001 to June 1, 2001 were regarded as historical data for the calibration of operational parameters of adaptive ramp-metering algorithms. Loop data of June 4 and June 5 of 2001 were used for the evaluation study. All of the input data (e.g., O-D demands) used in this study and the model calibration itself are manifest within the context of this currently operating metering algorithm; our assumption is that the basic input parameters would not change significantly under alternative metering strategies.

### ***Simulation Model Calibration***

PARAMICS regards each vehicle in the simulation as a Driver Vehicle Unit (DVU), and thus simulation relies on not only characteristics of drivers and vehicles but also the network geometry. Accurate and proper coding of the geometry of network is very important since drivers' behaviors in PARAMICS are very sensitive to network geometry. In addition, as the basic input data to the network model, the following parameters need to be prepared:

- (1) Proportion of each vehicle type on the studied section of freeway;
- (2) Vehicle characteristics and performance, such as the acceleration and deceleration rates of each type of vehicle;



- (3) Driving restrictions, such as the speed limits and driving lane restrictions for trucks;
- (4) Driver behavior (including aggressiveness and awareness) distribution, which is assumed to be normal distribution.

Since no local arterial street is included in the study network, route choice problem is not involved in our calibration process. Based on the above data and assumptions, the following aspects were further considered for model calibration:

- (1) The signposting setting for links, which defines the location of the weaving area if there are more than one link connecting with the downstream end of the link or there is a geometry change at the downstream end of the link;
- (2) The mean target headway and driver reaction time, two key user-specified parameters in the car-following and lane-changing models that can drastically influence overall driver behaviors of the simulation. The calibrated values of the two parameters were 0.9 and 0.6 seconds, respectively, in this study.

The calibration process is an iterative process with the objective function to minimize the difference of traffic counts at measurement locations between simulation and observation. Measurement locations include detector stations at all on-ramps, off-ramps, and mainline detector stations. The calibration results for freeway loop stations located at post-mile 1.93, 3.04, 3.86, and 5.55 (one station at each junction) are presented in Figure 3. Observed and simulated traffic counts at these stations are compared at 5-minute intervals over the whole simulation period. The measure of goodness of fit used to quantify the relationship between the observed and simulated measurements is Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{T} \sum_{t=1}^T [|M_{obs}(t) - M_{sim}(t)| / M_{obs}(t)] \quad (1)$$

where  $M_{obs}(t)$  and  $M_{sim}(t)$  are observed and simulated traffic counts of time period  $t$ ;  $T$  is the number of measurement points (over time in this case). The values of MAPE of these four loop stations range from 5.5% to 9.8%. Therefore, simulated traffic counts correspond well to the measurements and accurately capture the temporal patterns in traffic flows. We also draw the volume-occupancy diagrams (for both simulated and observed) of the mainline detector station at post-mile 3.04, shown in Figure 4. Both diagrams have a similar trend, whose occupancy at capacity is in the neighborhood of 20%.

## Adaptive Ramp Metering Algorithms

In this section, we provide the descriptions and parameter calibrations of the three ramp-metering algorithms that were evaluated: ALINEA, BOTTLENECK, and ZONE, as well as versions of BOTTLENECK and ZONE modified to incorporate ALINEA as the local controller.

### *The ALINEA algorithm*

As a local feedback ramp metering policy (Papageorgiou et al 1991), the ALINEA algorithm attempts to maximize the mainline throughput by maintaining a desired occupancy on the downstream mainline freeway. Two detector stations are required for the implementation of the ALINEA algorithm. The first loop detector is located on the mainline freeway, immediately downstream of the entrance ramp, where the congestion caused by the excessive traffic flow originated from the ramp entrance can be detected. The second loop station is on the downstream end of the entrance ramp, and used for counting the on-ramp volume.

For an on-ramp under ALINEA control, its metering rate during time interval  $(t, t + \Delta t)$  is calculated as:

$$r(t) = \tilde{r}(t - \Delta t) + K_R \bullet (O^* - O(t - \Delta t)) \quad (2)$$

where  $\Delta t$  is the update cycle of ramp metering implementation;  $\tilde{r}(t - \Delta t)$  is the measured metering rate of the time interval of  $(t - \Delta t, t)$ ;  $O(t - \Delta t)$  is the measured occupancy of time interval  $(t - \Delta t, t)$  at the downstream detector station;  $K_R$  is a regulator parameter, used for adjusting the constant disturbances of the feedback control;  $O^*$  is the desired occupancy at the downstream detector station. The value of  $O^*$  is typically set equal to or slightly less than the critical occupancy, or occupancy at capacity, which can be found in the volume-occupancy relationship.

### ***The BOTTLENECK Algorithm***

The BOTTLENECK algorithm has been applied in Seattle, Washington for several years (Jacobsen et al, 1989). Basically, there are three components in the algorithm: a local algorithm computing local-level metering rates based on local conditions, a coordination algorithm computing system-level metering rates based on system capacity constraints, and adjustment to the metering rates based on local ramp conditions.

The local metering algorithm employed by the BOTTLENECK algorithm is occupancy control. The metering rate for the occupancy control is selected from a predetermined, finite set of discrete metering rates, on the basis of occupancy levels upstream of the given metered ramp. Historical data collected from the given detector station are used to approximate volume-occupancy relationships, which will be used to calculate the predetermined set of metering rates.

The coordination algorithm is the unique aspect of BOTTLENECK. The freeway segment under control is divided into several sections, each of which is defined by the stretch of freeway between two adjacent mainline loop stations. A section is identified as a bottleneck if it satisfies two conditions, i.e. capacity condition and vehicle storage condition. The capacity condition can be described as:

$$O_{down}(i, t) \geq O_{thresh}(i) \quad (3)$$

where  $O_{down}(i, t)$  is the average occupancy of the downstream detector station of section  $i$  over the past one-minute period  $(t-1, t)$ ;  $O_{thresh}(i)$  is a pre-defined loop station occupancy threshold when it is operating near capacity. The vehicle storage condition can be formulated as:

$$\tilde{Q}(i, t) = (Q_{up}(i, t) + Q_{on}(i, t)) - (Q_{off}(i, t) + Q_{down}(i, t)) \geq 0 \quad (4)$$

where  $\tilde{Q}(i, t)$  is the number of vehicles stored in section  $i$  during the past minute.  $Q_{up}(i, t)$  and  $Q_{down}(i, t)$  are the volume entering section  $i$  across the upstream detector station and the volume exiting section  $i$  across the downstream detector station during the past minute, respectively;  $Q_{on}(i, t)$  is the total volume entering section  $i$  from on-ramps during the past minute;  $Q_{off}(i, t)$  is the total volume exiting section  $i$  to off-ramps during the past minute.

The number of vehicles stored in the bottleneck section  $\tilde{Q}(i, t)$  should be reduced. Each section needs to define an area of influence that consists of a number of upstream on-ramps for the volume reduction. The amount of volume reduction from an on-ramp is determined by a weighting factor, pre-defined according to how far it is to the downstream detector station of the bottleneck section and the historical demand pattern from the on-ramp. If on-ramp  $j$  involves in the volume reduction of any bottleneck section, its system-level metering rate is calculated as:

$$r(j, t) = Q_{on}(j, t-1) - \underset{i=1}{\overset{n}{MAX}}(\tilde{Q}(i, t) \bullet WF_{j,i} / \sum_j WF_{j,i}) \quad (5)$$

where  $\underset{i=1}{\overset{n}{MAX}}$  is defined as the operator of selecting the maximum volume reduction if the on-ramp is located within more than one section's area of influence.  $Q_{on}(j, t-1)$  is the entrance volume from on-ramp  $j$  during the past minute;  $WF_{j,i}$  is the weighting factor of on-ramp  $j$  within the area of influence for section  $i$ ;  $\tilde{Q}(i, t) \bullet WF_{j,i} / \sum_j WF_{j,i}$  is the volume reduction of on-ramp  $j$  because of section  $i$ .

The more restrictive of the local rate and the system rate will be selected for further adjustments, including queue adjustment, ramp volume adjustment and advanced queue override. The queue adjustment and advanced queue override are used for preventing traffic spillback onto arterials. Ramp volume adjustment copes with the condition that more vehicles have entered the freeway compared to the number of vehicles assumed to enter, which may be caused by HOV traffic or HOV lane violators. The metering rate to be finally implemented should be within the range of the pre-specified minimum and maximum metering rates.

### ***The ZONE Algorithm***

The ZONE algorithm has been applied successfully in the Minneapolis/St. Paul area, Minnesota (Lau 1997). The ZONE algorithm needs to first identify critical bottlenecks of the target directional freeway network, and then divides the entire network into multiple zones. For each zone, its upstream boundary is usually a free-flow area and its downstream boundary is a critical bottleneck. Each zone has a typical length of 3 to 6 miles and may contain several metered or non-metered on-ramps and off-ramps. The basic concept of the algorithm is volume control, i.e. balancing the traffic volume entering the zone with the traffic volume leaving the zone. The volume control equation is:

$$M + F = X + B + S - (A + U) \quad (6)$$

where  $M$  is the total metered ramp volumes,  $F$  is the total metered freeway-to-freeway ramp volumes;  $X$  is the total measured off-ramp volumes;  $B$  is the downstream bottleneck volumes at capacity;  $S$  is the space available within the zone, which can be estimated based on measured occupancy values of mainline detectors inside the zone;  $A$  is the measured upstream mainline volume;  $U$  is the total measured non-metered ramp volumes. Here,  $X$ ,  $S$ ,  $A$  and  $U$  are measured

variables,  $M$  and  $F$  are controlled variables, and  $B$  is treated as a constant, usually 2200 vehicles per hour per lane.

The typical historical traffic volumes during the peak hour are used for the calculation of the metering rate look-up table. According to the total allowed on-ramp volume, the look-up table includes five 5-min volume thresholds, corresponding to six distinct levels of metering rates for each on-ramp within a zone. During the operation of the ramp-metering algorithm, the value of measured variable  $(X + B + S - A - U)$  will be compared with these volume thresholds in order to find an appropriate metering level for every metered ramp within the zone.

Besides the volume control aspect of the algorithm, ZONE also integrates an occupancy control strategy in order to consider localized congestion. Each ramp meter is assigned loop stations up to three miles downstream for occupancy control. The more restrictive metering rate of volume control rate and occupancy control rate is always selected for operation.

### ***The Revised BOTTLENECK and ZONE Algorithms***

Originally, both BOTTLENECK and ZONE algorithms incorporate occupancy control as their local controllers to account for the localized congestion. Comparing with ALINEA, occupancy control is a feed-forward control strategy known to be not as robust as such feedback control strategies as ALINEA. We should also note that the selected metering rate for occupancy control is on the basis of occupancy levels upstream of a given metered ramp, whereas the calculated metering rate from ALINEA is based on the desired occupancy on the downstream mainline freeway. So ALINEA should react faster than the occupancy control strategy for the downstream congestion of a given ramp. In addition, the calibration of occupancy control is somewhat awkward. This is primarily manifest in terms of the determination of the set of discrete metering rates corresponding to different levels of upstream occupancy from the

historical volume-occupancy relationship. Therefore, to further evaluate the performance of the coordinated algorithms, we also implemented two revised algorithms, a revised BOTTLENECK and a revised ZONE algorithm, in which their native occupancy control strategies are replaced by ALINEA. We refer to the two revised algorithms as BOTTLENECK-ALINEA and ZONE-ALINEA.

### ***Calibration of Algorithms***

The calibrated parameters of the ALINEA algorithm are shown in Table 2. Based on reported practices (Papageorgiou et al. 1991 and 1997), the regulator parameter was set to 70 vph. Since the aggregation cycle of loop detector data is 30 seconds from the field, the metering update cycle was set to 30 seconds in this study in order to quickly feedback the variation of mainline traffic to the ramp control. The location of downstream detector station and the desired occupancy were further determined according to our own calibration experiments and sensitivity analysis on the target network.

For the BOTTLENECK algorithm, we defined a freeway section as the segment between two adjacent mainline detector stations currently existing in the real world. We also assumed that on-ramps in the area of influence should be within a maximum distance of two miles to the downstream boundary of each section. As a result, there are thirteen sections in the study area. Each section has a pre-defined area of influence, shown in Figure 5. The weighting factors of each on-ramp in the area of influence of each section (shown in Table 3) were calculated based on typical historical demand pattern during the peak hour. In addition, the occupancy thresholds in the occupancy control strategy were calibrated based on a plot of historical volume-occupancy data collected at corresponding measurement location. Since data collected from all upstream

detector stations show a similar trend in their respective volume-occupancy diagrams (see Figure 4 as an example), the same occupancy control plan is applied to all on-ramps, shown in Table 4.

For the ZONE algorithm, we found two major bottlenecks in the study network based on the analysis of historical loop data. The first bottleneck is located at post-mile 2.35, caused by lane drop and high entry volume from freeway SR-133. The second bottleneck is located at the merge area with on-ramp 5. Therefore, we defined two zones for the study network. The first zone is from post-mile 0.6 to 2.35, which includes on-ramps 1 and 2. The second zone is from the downstream of post-mile 2.35 to the downstream merge area of on-ramp 5, which includes on-ramps 3, 4 and 5. Since no zone covers on-ramps 6 and 7, they are under occupancy control, whose metering plans are shown in Table 4. The metering cycle look-up table that includes volume control and occupancy control plans of the two zones is shown in Table 5.

The metering rates from all above algorithms need to be finally adjusted based on the on-ramp volume restriction, queue override, and HOV adjustment strategies. The on-ramp volume restriction requires the implemented metering rate to be limited within some pre-defined maximum and minimum values. The queue override strategy in our study uses a queue detector located at the  $\frac{3}{4}$  total length of the entrance ramp for detecting excessive queue lengths. As soon as the occupancy of the queue detector exceeds a certain threshold (50% in our study), the metering rate will be set to a maximum value to avoid interference with the traffic on the surface street. Though the queue override strategy is not involved in the implemented ZONE algorithm in the real world, we integrate it to the ZONE algorithm in our study for the evaluation purposes. In addition, if there exists an un-metered HOV bypass lane on the entrance ramp, the metering rate of the on-ramp will be adjusted by the HOV volume. In this paper, we set a fixed 15% of total vehicles as HOV vehicles in the simulation.



## **Evaluation Studies**

### ***Measures of Effectiveness (MOEs)***

Three measures of effectiveness are used to evaluate ramp-metering algorithms:

MOE #1: Vehicle-Hours Traveled (VHT), which is a measure of overall system performance for the whole network. All vehicles, including those having finished their journey and those currently simulated, are all considered in this measure.

MOE #2: Average mainline travel time (AMTT), which is a measure of traffic conditions on the mainline freeway (from the upstream end to the downstream end of the freeway) within the whole simulation process.

MOE #3: Total on-ramp delay (TOD), which is a measure of the effects of ramp control to the on-ramp traffic flows. The measure is calculated by the sum of the difference of the actual travel time and free flow travel time that all vehicles experienced on the entrance ramps.

### ***Evaluation Scenarios***

The ramp-metering algorithms were evaluated under four scenarios: heavily congested morning peak-hour scenario (Scenario #1), less congested morning peak-hour scenario (Scenario #2), severe incident scenario (Scenario #3) and less severe incident scenario (Scenario #4). The OD demands of scenario #1 and #2 were estimated based on two different days' loop data, which show that the total traffic volume generated from the upstream end of the freeway under scenario #1 (based on loop detector data of June 5, 2001) is 6% higher than that of scenario #2 (based on loop detector data of June 4, 2001). The revealed pattern of recurrent traffic congestion from loop detector data is that freeway traffic cannot keep free flow speed (65mph in this study) from 7:30 to around 9:00 AM under scenario #1 and from 7:45 to around 8:30 under scenario #2. Both

of the two incident scenarios have the same OD demands as scenario #2, and an incident blocking the rightmost lane for 10 minutes at the location upstream of entrance ramp 4, which produce a new bottleneck to the target network. Comparing scenario #3 and #4, scenario #3 has an incident happened at the beginning of the recurrent congestion (at 7:45 AM) and thus causes a more severe congestion than scenario #4, which has an incident at the end of the recurrent congestion (at 8:20 AM). The non-recurrent traffic congestion patterns under two incident scenarios from simulations show that freeway traffic cannot keep free flow speed from 7:45 to around 9:15 AM under scenario #3 and from 7:45 to around 8:50 under scenario #4.

Fifteen Monte Carlo simulation runs were conducted under each scenario. For each simulation run, the first 10 minutes were treated as the “warm-up” period, and not taken into the result analysis. The 10-minute “warm-up” period was regarded as the transient phase for the traffic network from empty to initial steady-state condition. The simulation time periods for all four scenarios were morning peak hours from 6:30 to 10:00 a.m.

### ***Results and Discussions***

As we described in the above sections, three adaptive algorithms, ALINEA, BOTTLENECK and ZONE, and two revised algorithms, BOTTLENECK-ALINEA and ZONE-ALINEA were evaluated in this study. The fixed-time metering control was regarded as the baseline of this study. All evaluated adaptive ramp-metering algorithms were compared to the fixed-time control.

The performance measures of algorithms evaluated under recurrent congestion conditions, i.e., the first two scenarios, are shown in Table 6. It is found that all evaluated ramp-metering algorithms can improve freeway congestion under both scenarios. The system performance of adaptive ramp-metering control under scenario #1 is much better than that under scenario #2,

which implies that the effectiveness of the adaptive ramp control depends on the level of congestion on the freeway. As long as the target level of service (LOS) could be maintained through the regulation of ramp meters, the more congested the traffic condition is, the more effective the adaptive ramp metering control can be. However, if the congestion becomes severe and the target LOS could not be maintained by using ramp metering, the effectiveness of adaptive ramp control is marginal. This is illustrated in Table 6. The improvement of system performance under ramp control is not significant for both incident scenarios; especially under scenario #3 because the incident was injected at the beginning of the recurrent congestion, therefore caused more severe and longer congestion.

To further investigate and better understand the performance of each algorithm, Figure 6 and 7 compare the vehicle-hours traveled and average mainline travel time, respectively. ALINEA shows good performance under all scenarios despite that ALINEA is only a local feedback control strategy. The traditional ZONE and BOTTLENECK algorithms do not show better performance than ALINEA although both ZONE and BOTTLENECK are area-wide coordinated algorithms. However, the simulation results show that the revised BOTTLENECK and ZONE algorithms, in which ALINEA replaces the occupancy control algorithm as the local control strategy, perform much better than the traditional BOTTLENECK and ZONE algorithms. They are also more efficient than ALINEA under recurrent congestion. This implies the importance of good local control in a coordinated algorithm. As we described in the previous section, ALINEA is a better local control strategy than occupancy control, therefore helps the coordinated algorithms to achieve greater performance.

All ramp-metering algorithms improve the whole system performance by imposing a certain amount of delay on vehicles from entrance ramps. Figure 8 compares the total on-ramp

delay for each algorithm under all scenarios. In nearly all test scenarios, ALINEA causes modest delay to on-ramp vehicles, but its reduction to mainline travel time is also modest (see Figure 6 and 7). In contrast, under Scenario #1 and #2, the revised ZONE algorithm causes very high delay to on-ramp vehicles, yet it also produces the largest reductions in mainline travel time. The overall effectiveness of a metering algorithm in reducing system delay depends on the trade-off between ramp and mainline delays.

Coordinated control algorithms are capable of identifying bottlenecks and responding to congestion initiated by these bottlenecks. Although most bottlenecks in the real world have fixed locations (such as merges and lane-drops), some bottlenecks arise dynamically and change from location to location (such as incident-induced bottlenecks). Conceptually, the BOTTLENECK algorithm can work with dynamic bottlenecks; ZONE can work with fixed bottlenecks only, which need to be identified during the pre-implementation phase based on historical traffic conditions. Consequently, the BOTTLENECK algorithm should perform better than the ZONE algorithm under incident conditions. This is confirmed by our simulation results of the revised BOTTLENECK and ZONE algorithms. As shown in Table 6 and 7, the revised BOTTLENECK algorithm performs better than the revised ZONE algorithm under the incident scenarios (Scenario #3 and #4), but the revised ZONE algorithm performs better or equivalent to the revised BOTTLENECK algorithm under scenario #1 and #2 that have no dynamic bottlenecks, i.e., recurrent congestion. It should be recognized that the identification of dynamic bottlenecks in the BOTTLENECK algorithm is still a reactive, not proactive process, and heavily dependent on accurate traffic volume information from the detectors.

## Conclusions and Future Works

This paper illustrated a micro-simulation method to evaluate the performance of three adaptive ramp-metering algorithms, ALINEA, BOTTLENECK and ZONE, and two revised algorithms, BOTTLENECK-ALINEA and ZONE-ALINEA. The evaluation has been conducted in capability-enhanced PARAMICS simulation environment over a stretch of the I-405 freeway in California, under both recurrent congestion and incident scenarios. Simulation models were calibrated using the loop detector data collected from the field. Findings from this study can be summarized as follows:

(1) Simulation results show that adaptive ramp-metering algorithms can improve freeway congestion effectively compared to the fixed-time control; however, ramp metering becomes less effective when traffic experiences severe congestion under incident scenarios.

(2) Comparing three algorithms, ALINEA achieves the reductions of freeway travel time under both recurrent and non-recurrent congestion scenarios while maintaining modest delay for on-ramp vehicles. Both original BOTTLENECK and ZONE algorithms fail to show better performance than ALINEA, despite that both of them are area-wide coordinated algorithms, and the efforts for the calibration of their parameters are much higher.

(3) The two coordinated ramp-metering algorithms, BOTTLENECK and ZONE, can be improved by replacing their native local control algorithms with ALINEA. Simulation results show that the revised algorithms, BOTTLENECK-ALINEA and ZONE-ALINEA, perform better than the original algorithms, and are more efficient than ALINEA alone.

(4) The BOTTLENECK algorithm can work with dynamic bottlenecks whereas the ZONE algorithm requires the location of bottleneck to be identified a priori from historical data. The process of identifying bottlenecks could be time-consuming and expensive since it involves

detailed analysis of traffic patterns. Simulation results show that the BOTTLENECK algorithm performs much better than the ZONE algorithm under incident scenarios, which usually feature dynamic bottlenecks.

(5) Overall, the revised BOTTLENECK algorithm performs robustly under all scenarios.

Since our simulation network does not contain arterial routes, traffic diversion to alternative routes is not considered and thus the performance improvement through ramp metering control is not fully revealed. Ideally, one should consider a corridor network and integrate a variety of control measures, including ramp metering, traffic diversion, and signal timing, to combat traffic congestion. We should also note that all of the algorithms evaluated in this study are reactive, rather than proactive, control strategies. Algorithms with state estimation and/or OD prediction capabilities are desirable. The development and evaluation of these integrated control strategies will be left to future studies.

## **Acknowledgements**

This research was funded by the California Department of Transportation (Caltrans) through the California Partners for Advanced Transit and Highways (PATH) Program and the ATMS Testbed Research Program. The opinions expressed in this paper are those of the writers. Thanks are also due to the anonymous referees whose comments and suggestions improved the quality of this paper.

Scott Aitken and Ewan Speirs, from Quadstone in Scotland, provided invaluable technical supports in the process of applying the PARAMICS model. Their continuous collaboration to the project greatly facilitated the work.

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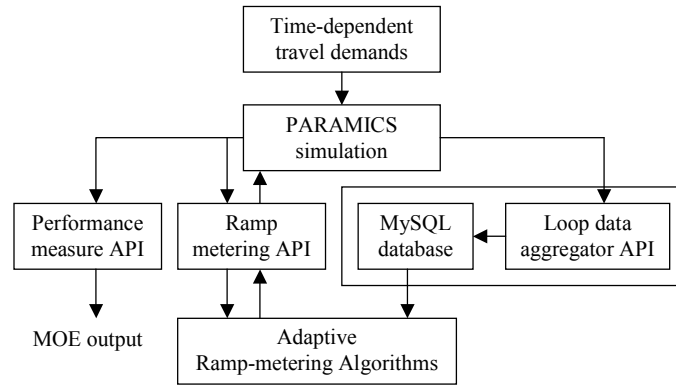


Figure 1. Simulation environment for the evaluation of adaptive ramp-metering algorithms

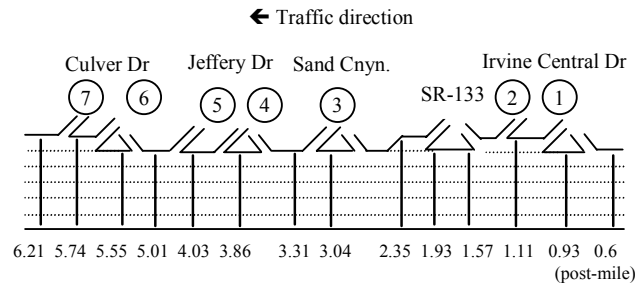


Figure 2. Schematic layout of the study site including seven metered on-ramps

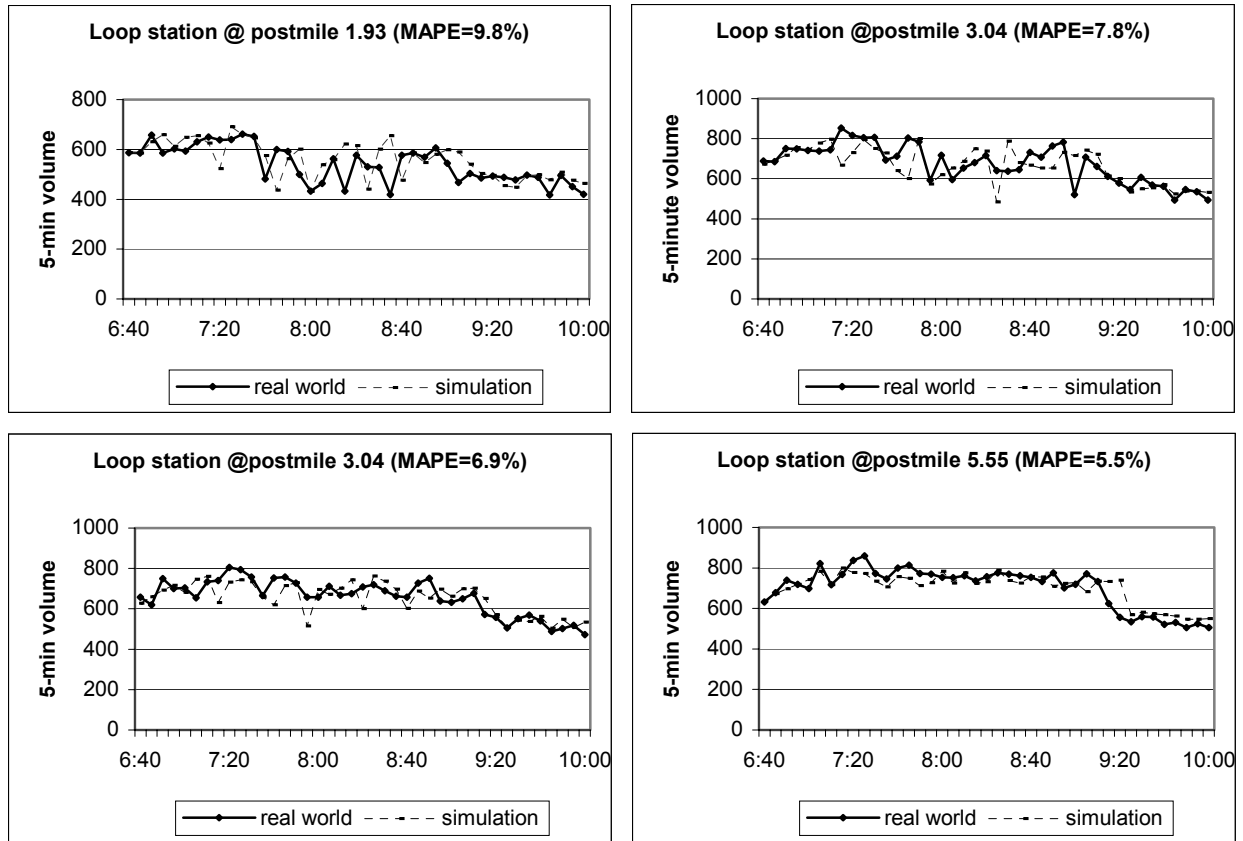


Figure 3. Comparison of volume data from simulation and real world

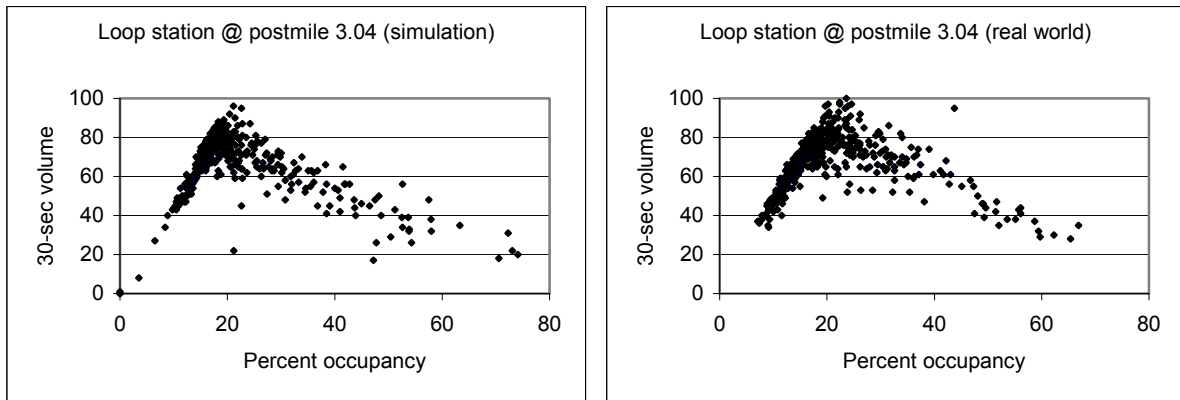


Figure 4. Comparison of volume-occupancy relationships from simulation and real world

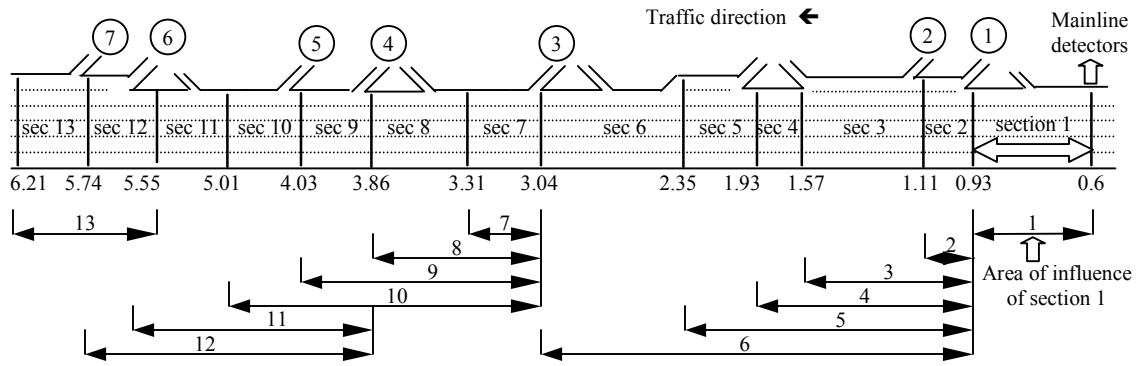


Figure 5 Definition of area of influence for each section in the Bottleneck algorithm

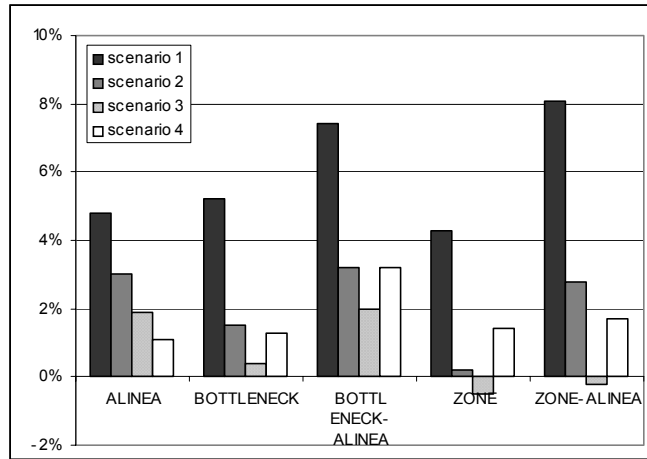


Figure 6 Comparison of the time saving of vehicle-hours traveled

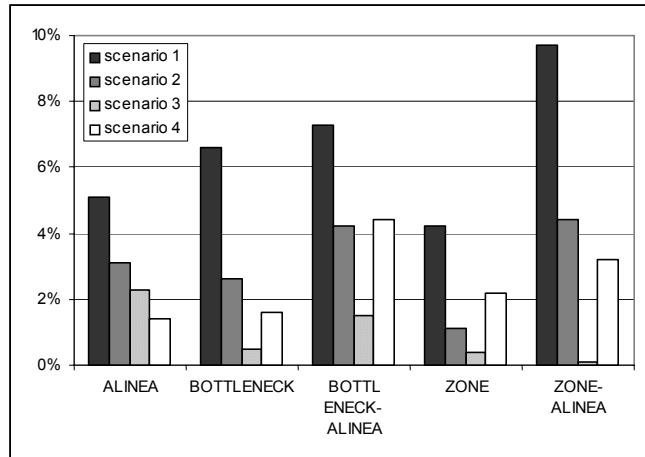


Figure 7 Comparison of the time saving of average mainline travel time

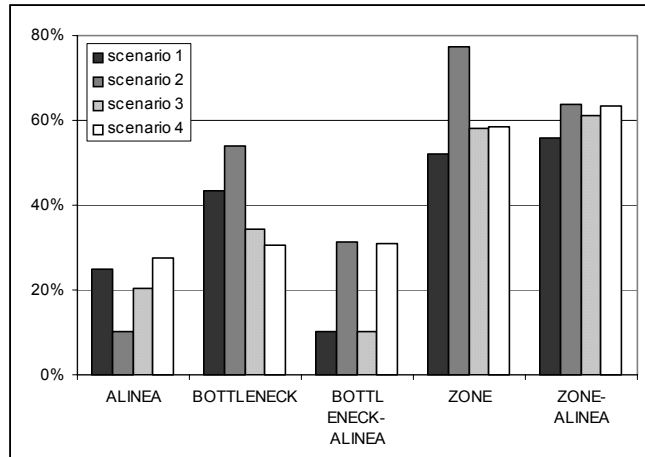


Figure 8 Comparison of the increase of total on-ramp delay



Table 1 Fixed-time metering plan currently deployed in the study area

Entrance ramp #	Metering cycle (sec.)	
	6-9 AM	3-7 PM
1	6	6
2	12	7
3	5	4
4	7	7
5	5	6
6	6	6
7	7	6

Table 2. Calibrated parameters for the ALINEA algorithm

Calibrated parameters	Calibrated values
Location of downstream detector station	60 m
Desired occupancy	20%
Update cycle	30 seconds
Regulation parameter $K_R$	70 vph

Table 3 Calibrated weighting factors of the Bottleneck algorithm

Section #	Entrance ramp #						
	1	2	3	4	5	6	7
1	1.0	0	0	0	0	0	0
2	1.0	0	0	0	0	0	0
3	0.6	0.4	0	0	0	0	0
4	0.6	0.4	0	0	0	0	0
5	0.6	0.4	0	0	0	0	0
6	0.6	0.4	0	0	0	0	0
7	0	0	1.0	0	0	0	0
8	0	0	1.0	0	0	0	0
9	0	0	0.8	0.2	0	0	0
10	0	0	0.55	0.1	0.35	0	0
11	0	0	0	0.25	0.75	0	0
12	0	0	0	0.12	0.45	0.43	0
13	0	0	0	0	0	0.37	0.63

Table 4 Metering plan under occupancy control

Percent occupancy	Metering plan (Seconds / cycle)
$\leq 11\%$	4.0
11- 16%	6.0
17-22%	7.5
23-28%	10.0
29-34%	12.0
$\geq 35\%$	15.0

Table 5 Metering cycle look-up table for the ZONE algorithm

Metering Level		Occupancy threshold	5-min volume threshold	Metering cycle (sec)		
				Ramp #1	Ramp #2	
Zone 1	1	N/A	> 91	3.3	10.0	
	2	N/A	> 84	3.8	12.0	
	3	17-22	> 70	4.5	15.0	
	4	23-28	> 56	5.6	15.0	
	5	29-34	> 42	7.1	15.0	
	6	>= 35	< 42	10.0	15.0	
Metering Level		Occupancy Threshold	5-min volume threshold	Metering cycle (sec)		
				Ramp #3	Ramp #4	Ramp #5
Zone 2	1	N/A	> 224	3.8	6.9	2.6
	2	N/A	> 192	4.4	8.0	3.0
	3	17-22	> 160	5.1	9.4	3.5
	4	23-28	> 128	6.3	11.4	4.3
	5	29-34	> 96	8.1	14.8	5.5
	6	>= 35	< 96	11.3	15.0	7.7

Table 6 Performance measures under recurrent congestion conditions

Metering algorithm		VHT (hr.)	AMTT (sec.)	TOD (hr.)
Scenario 1	Fixed-time	4799	526.9	71.4
	ALINEA	-4.8%	-5.1%	24.9%
	BOTTLENECK	-5.2%	-6.6%	43.5%
	BOTTLENECK- ALINEA	-7.4%	-7.3%	10.3%
	ZONE	-4.3%	-4.2%	51.9%
	ZONE-ALINEA	-8.1%	-9.7%	55.9%
Scenario 2	Fixed-time	3777	413.6	48.4
	ALINEA	-3.0%	-3.1%	10.3%
	BOTTLENECK	-1.5%	-2.6%	53.8%
	BOTTLENECK-ALINEA	-3.2%	-4.2%	31.3%
	ZONE	-0.2%	-1.1%	77.5%
	ZONE-ALINEA	-2.8%	-4.4%	63.9%

Table 7 Performance measures under incident scenarios

Metering algorithm		VHT (hr.)	AMTT (sec.)	TOD (hr.)
Scenario 3	Fixed-time	4200	468.3	61.9
	ALINEA	-1.9%	-2.3%	20.3%
	BOTTLENECK	-0.4%	-0.5%	34.2%
	BOTTLENECK- ALINEA	-2.0%	-1.5%	10.3%
	ZONE	0.5%	0.4%	58.1%
	ZONE-ALINEA	0.2%	-0.1%	61.3%
Scenario 4	Fixed-time	4149	458.6	60.5
	ALINEA	-1.1%	-1.4%	27.5%
	BOTTLENECK	-1.3%	-1.6%	30.4%
	BOTTLENECK-ALINEA	-3.2%	-4.4%	30.9%
	ZONE	-1.4%	-2.2%	58.6%
	ZONE-ALINEA	-1.7%	-3.2%	63.3%